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FORECASTING BY (ARIMA) MODELS TOINFLATION RATE IN SUDAN

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ABSTRACT

In this paper we introduce a brief review about Box-Jenkins models. These models provide a very good method to forecast for stationary and non-stationary time series. Box and Jenkins technique is used to find the best model for inflation rates in Sudan. To achieve this objective, a series of inflation rates ranged from 1998 to 2013 were obtained from the annual reports of the Central Bank of Sudan. The estimation concludes that the most proper time series model to forecast the inflation rate in Sudan is the AR (1), MA (3) model. We find that the highest forecasted inflation rate in Sudan for the coming five years will be attained in 2020 as 109.37%.

INTRODUCTION

Inflation is an economic phenomenon that have attracted the attention of many economists and researchers. There is a wide variety of opinions among researchers on the causes of inflation and how it could be reduced. In this study, we address the problem of inflation in Sudan using Box-Jenkins models. Where we explain and interpret the behavior of the inflation phenomenon through time series analysis autoregressive moving average ARIMA, during the period 1998-2013. During this period, the Sudanese economy has passed through dramatic changes, due to the separation of southern Sudan, the change of the national currency, from dinar to pound and the rise of the Sudan's debt outstanding to the International Monetary Fund. Sudan has suffered from inflation during the nineties, where inflation rates have risen dramatically and continued to rise until 1997 at that time the inflation rate reached 130 %. The discovery of the oil in the south region of Sudan had a direct impact in reducing the inflation rate, where in 2007 the inflation rate is reduced to 8%. After the separation of southern Sudan in 2007, the inflation rate increased to 37% in 2013. The aim of the study is to find out a Box-Jenkins model based on annual series of inflation rate in Sudan for the period 1998-2013. This study is needed to accurately forecast the future in order to make right decisions concerning the Sudanese economy.

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MATERIALS AND METHODS

The ARIMA methodology developed by Box and Jenkins (BJ) (1970), allows us to find the best fit of a time-series model to past values of a time series. BJ

The Box-Jenkins

This methodology developed by G. E. P. Box and G. M. Jenkins, consists of four basic steps.

- Stationarity.
- Identification and estimation.
- Diagnostic checks.
- Forecasting univariate Model

Stationary

The classical Box – Jenkins models assumes that the time series stationary, if the time series is not stationary it can be converted to stationary one either by using the log or the reciprocal. The main properties of stationary series is:

(1) The mean is constant.
(2) The variance is constant.
(3) Constant autocorrelation structure.

To test whether the time series data are stationary or not the unit root test is used.

The augmented dickey-Fuller test ADF Hypothesis are:

The null hypostheis $H_0 : \rho = 0$
The alternative hypostheis $H_1 : \rho \neq 0$

If t-Statistic < ADF critical value, the null hypothesis is acceptable. (Unit root exist).

If t-Statistic > ADF critical value, the null hypothesis is not accep5table. (Unit root does not exist).

Model Identification and Estimation

In this section, we will discuss some of the important models that are useful in describing the data generation process of economic time series.

Autoregressive Processes

An AR process of order p (AR(p)) takes the following form

$$y_t = \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \mu_t \; \dots\dots (1)$$

Where $\mu_t$is an unobservable zero mean white noise process with time invariant variance $E(\mu_t) = \sigma^2{}_U$and the β_i are fixed coefficients. The process can be written in a more compact form by using the lag operator

$$\left(1 - \beta_1 L - \cdots - \beta_p L^p\right) y_t = \mu_t$$

$$or \quad \beta(L) y_t = \mu_t$$

Where $\beta(L) = 1 - \beta_1 L - \cdots - \beta_p L^p$ If α(z) ≠ 0 then the process is stable, where z is a complex number defined in the interval |z|≤ 1. Consequently, the process can be modeled as a linear combination of past errors,

$$y_t = \beta(L)^{-1} \mu_t = \varphi(L) \mu_t$$

$$= \mu_t + \sum_{j=1}^{\infty} \varphi_j \, \mu_{t-1}$$

Where the operator $\varphi(L)$ satisfies the condition $\beta(L)\varphi(L) = 1$, and $\varphi_j = \sum_{j=1}^{\infty} \varphi_{j-i} \, \mu_{t-1} \beta_i$for j = 1, 2,... with $\varphi_0 = 1 \; and \; \beta_i = 0$ for $i > p$. Such a process is called and MA process.

Moving Average Processes

For the case where the process y_t takes the form

$$y_t = \mu_t + m_1 \mu_{t-1} + \cdots + m_q \mu_{t-q} \dots\dots (2)$$

Where μ_t represent a zero mean white noise, the process is known as a moving average of order q (MA(q)). Such a process is always stationary, and it can be written in the following simple compact form

$$y_t = \left(1 + m_1 L + \cdots + m_q L^q\right) \mu_t$$

$$or \quad y_t = m(L) \mu_t$$

Where

$m(L) = 1 + m_1 L + \cdots + m_q L^q$. If $m(z) \neq 0$ for complex numbers z with $|z| < 1$, then the resultant MA representation is unique as well as invertible. In this case

$$m(L)^{-1} y_t = \beta(L) y_t$$

$$= y_t + \sum_{j=1}^{\infty} \beta_j \, y_{t-j} = u_t$$

Where $\beta(L) m\,(L) = 1$.

ARIMA Processes

A mixed ARMA process having AR of order p and MA of order q is denoted by ARMA (p, q) and it takes the representation

$$y_t = \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + m_1 \mu_{t-1} + \cdots + m_q \mu_t \dots \dots (3)$$

Equivalently this process could be written in the following compact form

$$\beta(L) y_t = \left(1 + m_1 L + \cdots + m_q L^q\right) \mu_t$$

$$or \quad y_t = m(L) \mu_t$$

Where $(L) = 1 - \beta_1 L - \cdots + \beta_q L^q$, when $m(z) \neq 0$ for $|z| \leq 1$, then the process is stable and stationary.

Note that, the stability of the process guarantee an existence of a pure (possibly infinite order) MA representation from which we can obtain the autocorrelations. In addition, the inevitability of the process results in a pure (infinite order) AR representation. In the case of mixed processes with nonzero AR and MA parts, the autocorrelations and partial autocorrelations approaches zero gradually

Diagnostic Checks

After the required model is obtained, the residuals of the actual values minus those estimated by, the model has to be checked. If such residuals are random, then the model is adequate. If not, another model has to be assumed and the process is repeated until we obtain a random residuals.

Forecasting Univariate Model

Quantitative forecasting methods are used when historical data are available, the most common types of quantitative forecasting methods are:

(1) The univariate models: These models predict future values of the variable of interest depending on the historical pattern of that variable, assuming the historical pattern will continue;
(2) The causal models: These models predict future values of the variable of interest depending on the relation between that variable and other variables.

Usually qualitative forecasting techniques are used when historical data are scarce or not available at all and depend on the opinions of experts

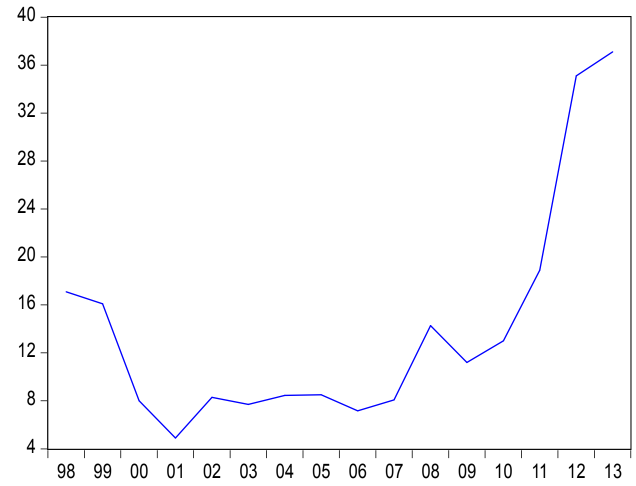
The factors that has to be considered in choosing a forecasting method are:

- The form in which the forecast is desire.
- The period of the forecasting situation.
- The pattern of data.

Other factors that might affect the choice of forecasting technique is the desired accuracy of the forecast, the availability of information and last the ease with which the forecasting method is operated.

RESULTS AND DISCUSSION

We will use the data set from the annual reports of the Central Bank of Sudan during the study period for our time series analysis. In this section, we will examine stationary series of Inflation Rate by unit root test (Augmented Dickey-Fuller Test, ADF) output from the (Eviwes) statistical software.



Source: Data analysis using (EVIWES) Software

Figure 1. series of inflation rate in Sudan for period (1998-2013)

Figure (1) shows that the inflation rate series is not stationary. There is an increasing trend.

Figure (2) shows that the last Q- Stat value is (28.127) with prob value (0.005)we reject the null hypothesis that the Inflation Rate series is not stationary, Also our spike of autocorrelation outside the line mean that the Inflation Rate series is not stationary.

Date: 04/11/15 Time: 14:33
Sample: 1998 2013
Included observations: 16

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.637	0.637	7.7874	0.005
		2	0.208	-0.33...	8.6780	0.013
		3	0.072	0.202	8.7923	0.032
		4	0.045	-0.08...	8.8411	0.065
		5	-0.02...	-0.06...	8.8585	0.115
		6	-0.16...	-0.17...	9.6157	0.142
		7	-0.20...	0.032	10.949	0.141
		8	-0.20...	-0.15...	12.464	0.132
		9	-0.20...	-0.01...	14.217	0.115
		1...	-0.22...	-0.14...	16.700	0.081
		1...	-0.26...	-0.11...	20.821	0.035
		1...	-0.24...	-0.05...	25.046	0.015

Figure 2. Corelegram of inflation rate in Sudan for period (1998-2013)

Table 1. Augmented Dickey-Fuller Test

Null Hypothesis: D(INF,2) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.927614	0.0001
Test critical values:	1% level	-2.754993	
	5% level	-1.970978	
	10% level	-1.603693	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 13

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INF,3)
Method: Least Squares
Date: 04/11/15 Time: 14:47
Sample (adjusted): 2001 2013
Included observations: 13 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INF(-1),2)	-1.505060	0.305434	-4.927614	0.0003

R-squared	0.668311	Mean dependent var	-0.546154
Adjusted R-squared	0.668311	S.D. dependent var	10.65634
S.E. of regression	6.137251	Akaike info criterion	6.540435
Sum squared resid	451.9903	Schwarz criterion	6.583892
Log likelihood	-41.51282	Hannan-Quinn criter.	6.531502
Durbin-Watson stat	2.074962		

Table (1) Shows that the computed ADF test-statistics -4.927614with prob value (0.0001)is less than 1%, 5% and 10% significant level respectively, the Durbin-Watson test is around 2, Determination coefficient is high R^2(0.66),therefore we reject H_0 and accept H_1 which mean that the Inflation Rate Series is stationary at the second difference

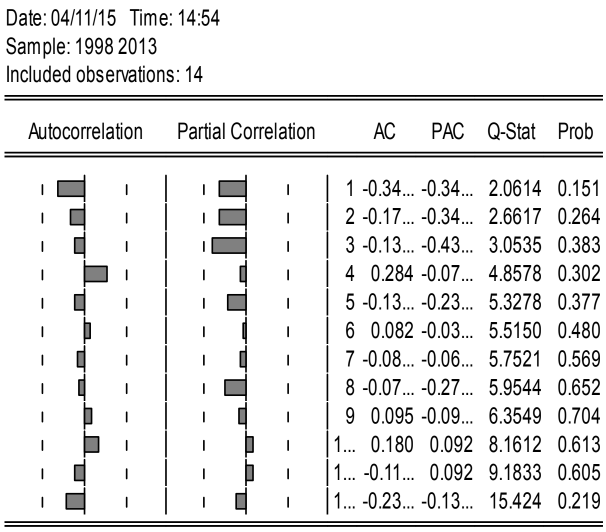


Figure 3. Seconddifference correlogram

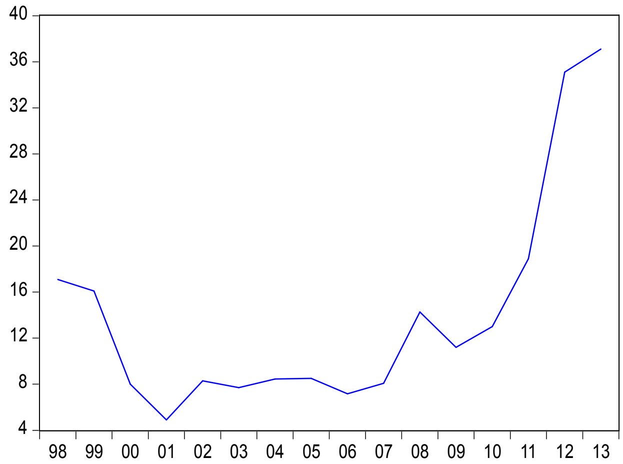


Figure 4. Second difference

Table 2. Model Estimation

Dependent Variable: INF
Method: Least Squares
Date: 04/11/15 Time: 15:15
Sample (adjusted): 1999 2013
Included observations: 15 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 1996 1998

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1.113441	0.142989	7.786899	0.0000
MA(3)	0.750188	0.137276	5.464801	0.0001

R-squared	0.703773	Mean dependent var	13.78533
Adjusted R-squared	0.680986	S.D. dependent var	9.817007
S.E. of regression	5.544777	Akaike info criterion	6.387156
Sum squared resid	399.6792	Schwarz criterion	6.481563
Log likelihood	-45.90367	Hannan-Quinn criter.	6.386150
Durbin-Watson stat	2.137389		

Source: Data analysis using (EVIWES) Software

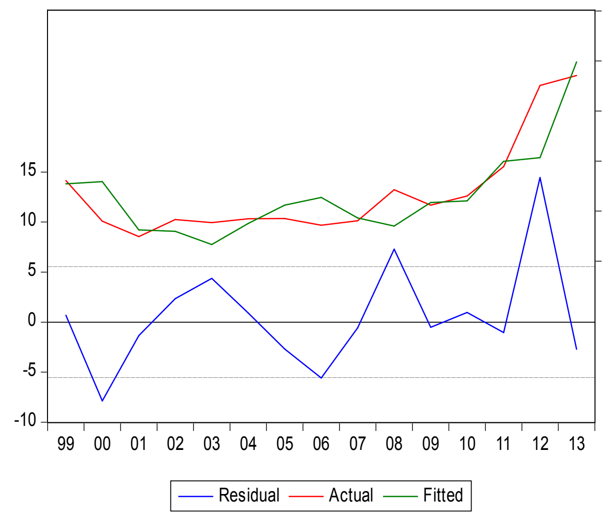


Figure 5. Fitted, Actual and Residual Dependent Variable DDINF

Table 3. Actual, Fitted the Inflation Rate series in Sudan

years	Actual Inflation	Fitted Inflation	Residual Inflation
1998	16.1000	15.4267	0.67327
1999	8.00000	15.8832	-7.88317
2000	4.90000	6.25517	-1.35517
2001	8.30000	5.96094	2.33906
2002	7.70000	3.32771	4.37229
2003	8.46000	7.55687	0.90313
2004	8.50000	11.1744	-2.67445
2005	7.16000	12.7443	-5.58429
2006	8.08000	8.64976	-0.56976
2007	14.2800	6.99027	7.28973
2008	11.2000	11.7107	-0.51067
2009	13.0000	12.0431	0.95688
2010	18.9000	19.9434	-1.04340
2011	35.1000	20.6609	14.4391
2012	37.1000	39.7996	-2.69963
2013	16.1000	15.4267	0.67327

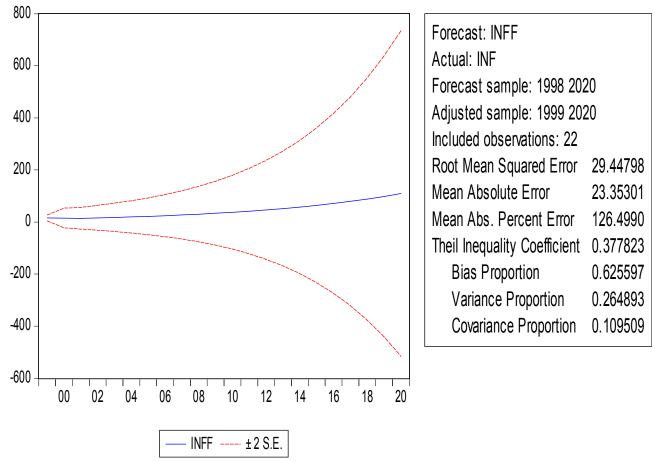


Figure 6. Forecasted Inflation Rate

Table 4. Forecasted Inflation Rate

Year	Forecasted Inflation Rate
2014	57.39847157
2015	63.90983081
2016	71.15984733
2017	79.23231541
2018	88.22053504
2019	98.22839030
2020	109.3715500

Figure(3) shows that the Prob. Increases as the lag increase, which is a good indicator for the absence of serial autocorrelation at the second difference. The last Q- Stat value is (15.424) with prob value (0.219) we accept the null hypothesis that the Inflation Rate series is stationary, Also our spike of autocorrelation within the line mean that the Inflation Rate series is stationary.

Figure (4): shows that Inflation Rate series is stationary at the second difference.

Model Estimation

We will use the second difference of the varibles from The stationary test for our Box-Jenkins (ARIMA) Models to estimaedthe model of Inflation Rate in Sudan by using the leat square method.The outputof the estimation from the (Eviwes) statistical software as:

Table (2) shows the estimated coefficients are statistically significant under a 5% level of significance. The overall regression fit, as measured by the R^2 statistics (R2=0.70377), indicate a good fit. Since the Durbin Watson value is (2.13738) which is around (2) it means that there is no serial autocorrelation. The Akaike, Schwarz criteria (6.38715, 6.48156) indicate that the AR (1), MA (3) model should be preferred because they have the least values among the different models which can be fitted. The Prob. (F-statistics=0.000000) indicate that the whole model is statistically significant under 5% level of significance.

The Estimation model from the table above can be written as:

Inf = [AR(1)=C(1),MA(3)=C(2),BACKCAST=1996]

Substituted Coefficients:

Inf = [AR (1)=1.11344,MA(3)=0.750188,BACKCAST=1996]

Figure (5) shows that the fitted values have no significant difference from the actual one.

Forecasting Ability Test

Before using the estimated model to forecast the process has to be predictive ability test. One of the most tests used in the ability of the model to forecasted the test unsteadiness of (Thiel Coefficient). If the value of Thiel coefficient close to zero indicated that the ability of the model to predict high. If approached Thiel coefficient value of one indicates that the inability of the model to predict

Figure (6) shows that the value of the Thiel Coefficient close to zero(0.377) indicated that the ability of the model to forecasted the Inflation Rate is high.

Tables (4) shows that the estimated and forecasted Inflation Rate is increasing.

Conclusion

1. In this paper we have estimated the inflation rate model in Sudan by using Box-Jenkins methodology (ARMA model). We find that the series is stationary in the second difference, and the best estimation model of inflation rate is AR (1), MA(3)
2. The value of the coefficient determination R^2 of the inflation rate model is (0.98) and this indicates the high quality of the model.
3. The estimated model satisfies the conditions of no serial correlation.
4. The ability of inflation rate model to predict the inflation rate in Sudan was then tested by using the (Thiel coefficient). We find that the estimated model ability of forecasting is very satisfactory and therefore it quite adequate to represent the inflation rate in Sudan
5. The model predict that the highest forecasted inflation rate in Sudan for the coming five years will be attained in 2020 as 109.371%

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